An Automated Synoptic Typing Procedure to Predict Freezing Rain: An Application to Ottawa, Ontario, Canada

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ABSTRACT

Freezing rain is a major weather hazard that can compromise human safety, significantly disrupt transportation, and damage and disrupt built infrastructure such as telecommunication towers and electrical transmission and distribution lines. In this study, an automated synoptic typing and logistic regression analysis were applied together to predict freezing rain events. The synoptic typing was developed using principal components analysis, an average linkage clustering procedure, and discriminant function analysis to classify the weather types most likely to be associated with freezing rain events for the city of Ottawa, Ontario, Canada. Meteorological data used in the analysis included hourly surface observations from the Ottawa International Airport and six atmospheric levels of 6-hourly NCEP–NCAR upper-air reanalysis weather variables for the winter months (Nov–Apr) of 1958/59–2000/01. The data were divided into two parts: a developmental dataset (1958/59–1990/91) for construction (development) of the model and an independent or validation dataset (1991/90–2000/01) for validation of the model. The procedure was able to successfully identify weather types that were most highly correlated with freezing rain events at Ottawa.

Stepwise logistic regression was performed on all days within the freezing rain–related weather types to analytically determine the meteorological variables that can be used as forecast predictors for the likelihood of freezing rain occurrence at Ottawa. The results show that the model is best able to identify freezing rain events lasting several hours during a day. For example, in the validation dataset, for likelihood values $\geq$0.6, the procedure was able to identify 74% of all freezing rain events lasting at least 6 h during a day. Similarly, the procedure was able to identify 91% of all freezing rain events occurring at least 8 h during a day. This study has further potential to be adapted to an operational forecast mode to assist in the prediction of major ice storms.

1. Introduction

Freezing rain is a major hazard that affects many parts of Canada; however, it is especially common in a corridor from Ontario to Newfoundland (Regan 1998; Stuart and Isaac 1999). In Ontario, freezing rain is most common in the Ottawa River valley when ‘‘warm’’ precipitation falls into a shallow subfreezing layer trapped within the valley basin. On average (for the period 1953/54–2000/01), Ottawa International Airport reported freezing rain 10 days a year, for a total of 38 h yr^{-1}. Of course, there are years when freezing rain is much more common; for example, during the winter of 1997/98, Ottawa received a total of 95 h of freezing rain. Sixty-five of these hours were recorded during the Ice Storm of 5–9 January 1998. During this extreme ice storm, freezing rain accumulations of close to 70 mm water equivalent were recorded in Ottawa (Milton and Bourque 1999). Regan (1998) reported that the ice storm was responsible for 25 fatalities, left some 1 million householders without power, caused nearly $3 billion (U.S. dollars) in damages, and resulted in another $3 billion in short-term lost economic output and insurance claims across Quebec and Ontario.

Given the potentially devastating impacts of major ice storms, there is considerable responsibility placed on forecasters to accurately predict these events with sufficient lead time to minimize property damage and loss of life and facilitate emergency responses. Much of the emphasis over the past few decades has been focused on improving the accuracy of short-term statistical and numerical prediction models to specify precipitation types. Bocchieri (1980) employed linear screening regression to derive relationships between parameters based on observed upper-air soundings and concurrent observations of precipitation type for the winter seasons (September through April) of 1972/73 through 1976/77. This model was able to correctly differentiate between liquid and frozen precipitation with an accuracy of 95% and 88%, respectively. However, the model only predicted 40% of the occurrences of freezing rain. In addition, for about 39% of the cases where the model predicted freezing rain, the actual pre-

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cipitation fell as either liquid rain or in the frozen state. Bocchieri (1980) noted that much of the model difficulty was in the freezing rain category, which included both freezing rain and freezing drizzle; the latter potentially occurring in the absence of an elevated warm layer. Huffman and Norman (1988) used a similar approach to distinguish winter precipitation types and also found that the regression model was more proficient at differentiating liquid and frozen precipitation (model $R^2 = 0.885$ and 0.862, respectively) compared to actual freezing rain occurrence ($R^2 = 0.331$).

Many previous studies have used critical values of the various meteorological parameters to determine when and where particular types of precipitation (e.g., snow, rain, freezing rain, ice pellets) would occur during a forecast period. For example, Keeter and Cline (1991) derived the critical thickness to forecast precipitation types in North Carolina. Bourgouin (2000) developed a vertical temperature profile area method to differentiate between precipitation types. This method derived critical values of areas for a layer warmer than 0°C extending above a surface-based layer of air colder than 0°C, thereby determining whether sufficient energy was available in the environment to melt or freeze hydrometeors. Cortinas et al. (2002) examined the quality of six precipitation-type forecasting algorithms (some of them are currently used by the U.S. National Weather Service), including those used in the Keeter and Cline (1991) and Bourgouin (2000) studies. Using numerical weather model output, the algorithms were evaluated during the winter of 2000/01 by operational meteorologists at the U.S. National Centers for Environmental Prediction (NCEP) Storm Prediction Center and Hydrometeorological Prediction Center. They determined that the forecast systems overpredicted snow and rain, but underpredicted freezing rain and ice pellets. The forecast accuracy for rain was found to be relatively good, whereas the accuracy of the ice pellet and freezing rain forecasts was significantly less so.

Model output statistics (MOS), a statistical postprocessing system for improvement of numerical weather prediction, has been employed for a number of years in both Canada and the United States for the prediction of various weather elements and phenomena (Glahn and Lowry 1972; Carter et al. 1989; Vislocky and Fritsch 1995; Antolik 2000; Allen and Erickson 2001; Vallée and Wilson 2002). A recent study (Allen and Erickson 2001) evaluated MOS performance for precipitation-type prediction using an independent sample from September 1999 through March 2000 for about 650 stations in the contiguous United States and Alaska. The MOS models performed very well on overall categorical precipitation-type forecasts; however, the accuracy of freezing rain forecasts was significantly lower. For example, the Heidke skill score and threat score, resulting from MOS for the initial 24 h after the 0000 UTC model runs, were approximately 0.86 and 0.20 for categorical precipitation-type and freezing rain forecasts, respectively (see section 5 for comparison with this study). The Heidke skill score and threat score are measures of relative accuracy ranging from 0 to 1, where 1 represents a perfect forecast (Stanski et al. 1989; Wilks 1995). The primary advantage of using MOS techniques is that it can account for systematic model biases and the reduced skill of the numerical model with increasing projection time (Carter et al. 1989).

Other studies, using a manual classification approach for synoptic weather patterns, have focused on relationships between the type and frequency of synoptic-scale weather patterns and freezing precipitation. Bernstein et al. (1998) investigated the location of freezing rain observations relative to surface weather features using a 3-yr dataset for the continental United States. They found that frequencies of freezing rain were evenly divided between Arctic and east coast air masses (~50% in each), while freezing rain was rarely observed with Gulf, Pacific, or west coast air masses. In a recent study, Rauber et al. (2001) also employed a manual classification approach, using the 25-yr period from 1970 to 1994, to identify seven archetypal weather patterns associated with freezing precipitation in the continental United States. Seventy-four percent of freezing precipitation occurred in the following four distinctive weather patterns: 1) Arctic front–anticyclone, 2) cyclone–anticyclone, 3) warm front–occlusion sector of a cyclone, and 4) the west quadrant of Arctic high pressure. However, their techniques were based on a manual evaluation of daily surface weather maps, which can be exceedingly time consuming and data intensive when using a climatological period covering many years for a number of locations.

Over the past decade, automated synoptic typing approaches have become popular for an evaluation of the impact of climate on environmental issues, particularly since these methodologies characterize similarities in active meteorological elements within a holistic framework (Kalkstein et al. 1987). Environmental issues treated using these methodologies include air quality (Kalkstein and Corrigan 1986; Eder et al. 1994; McGregor and Bamzelis 1995; Lam and Cheng 1998; Cheng and Lam 2000), human health (Kalkstein 1991; Cheng 1991; Kalkstein et al. 1997; McGregor et al. 1999), and climate research (Kalkstein et al. 1990; Cheng and Kalkstein 1993, 1997). To date, the automated synoptic typing approach has shown considerable worldwide success for the prediction of air pollution concentrations and heat-related mortalities. However, it appears that this strictly automatic approach has not been applied to the assessment and prediction of freezing rain events. The objective of this study, therefore, was to develop a new method—a quantitative, automated synoptic typing—to assess and predict air masses or weather types most highly associated historically with freezing rain events. Within-synoptic-type logistic regression analysis was applied to predict the likelihood of freezing rain occurrence for the study area.

2. Data sources and treatment

Hourly surface meteorological data for Ottawa International Airport were retrieved from Environment Canada's Digital Archive of Canadian Climatological Data for the winter months (November–April) of 1958/59–2000/01. The meteorological data used in this study included hourly weather station observations of air temperature (°C), dewpoint temperature (°C), sea level air pressure (hPa), total cloud cover (tenths of sky cover), wind speed (m s^{-1}), wind direction (degrees), and occurrence of freezing rain (1 for yes or 0 for no). A sine–cosine transformation was used to convert wind speed and direction into southerly and westerly scalar velocities. With the exception of freezing rain occurrence, missing data were interpolated using a temporal linear method when the data were missing for three consecutive hours or less; otherwise, days with data missing for four or more consecutive hours were excluded from the analysis. For Ottawa, only 0.04% of the total hours required missing data interpolation; after interpolation, the dataset was 100% complete.

The 6-hourly upper-air reanalysis weather data were retrieved from the NCEP Web site. The reanalysis data (Kalnay et al. 1996; Kistler et al. 2001) were available daily for 0600, 1200, 1800, and next day 0000 UTC for the period 1958–2001 and included a variety of meteorological variables on a 2.5° × 2.5° latitude–longitude grid at 17 standard upper-air pressure levels, including air temperature (°C), relative humidity (%), geopotential height (m), vertical velocity (Ω, Pa s^{-1}), and west–east and south–north wind velocities (m s^{-1}). Data from only six pressure levels: 1000, 925, 850, 700, 600, and 500 hPa were used in this study since the atmospheric parameters needed to determine both production and type of precipitation are primarily confined to levels below 500 hPa. Although the reanalysis data were available for the entire 54-yr period 1948–2001, only the data for the period 1958–2001 were used in this study. Prior to 1958, the reanalysis data were based on observations taken 3 h later than the current synoptic time (e.g., 0300, 0900, 1500, and 2100 UTC) (Kistler et al. 2001). This is not consistent with the reanalysis data after 1958, which are valid for the same hours that observations were taken (e.g., 0000, 0600, 1200, and 1800 UTC).

For this study, the NCEP–National Center for Atmospheric Research (NCAR) reanalysis relative humidity data field was converted into dewpoint temperature based on Tetens' equation (Berry et al. 1945). Dewpoint temperature was preferred over relative humidity since it is highly conservative on a diurnal level and moderately conservative among various microenvironments (Kalkstein and Corrigan 1986). In order to combine the gridded reanalysis data with the surface weather data, the reanalysis data were interpolated for the Ottawa International Airport site using the inverse-distance method (Shen et al. 2001).

In order to create two independent datasets, the surface and upper-air reanalysis weather data were divided into two parts: a developmental dataset (1958/59–1990/91) used for construction of the model and a validation dataset (1991/92–2000/01) used to test the model.

3. Analysis techniques

a. Automated synoptic typing

An automated synoptic typing procedure, based primarily on airmass differentiation, was used to assign every day of the developmental dataset to a distinctive weather type. Thus, the surface weather data at 24 different times and six different weather elements produced 144 surface weather variables. The upper-air reanalysis data at 6-h intervals and six atmospheric levels produced 96 upper-air weather variables. The entire suite of 240 surface and upper-air weather variables was used in the synoptic typing procedure.

This synoptic typing procedure produces a temporal synoptic index using principal components analysis (PCA; Jolliffe 1986) and a hierarchical agglomerative clustering procedure. Since the number of weather types is not predetermined, a hierarchical agglomerative clustering procedure is suitable for this study (Kalkstein et al. 1996a,b; Cheng and Kalkstein 1997; Cheng and Lam 2000). The correlation-matrix-based PCA was used and each weather variable X_k was standardized (since the units of the various weather elements are not commensurate) using the expression

$$X_k(\text{standardized}) = \frac{X_k - \overline{X}_k}{\text{Std}}, \tag{1}$$

where $\overline{X}_k$ is the mean and Std is the standard deviation for each variable over the period 1958/59–2000/01 (Jolliffe 1986; Applequist et al. 2002). The PCA is able to reduce the 240 intercorrelated weather variables into a small number of linearly independent component variables, which can explain much of the variance within the original dataset. Component loadings were calculated to express the correlation between the original weather variables and the newly formed components. The number of principal components with eigenvalues greater than one was retained to calculate component scores. Days with similar meteorological situations tended to exhibit similar component scores. The average linkage clustering procedure generated statistical diagnostics to produce an appropriate number of clusters (see section 4a for details), and then classified those days with similar component scores into one of the meteorologically homogenous groups. A variety of statistical tests was used to determine the number of clusters for retention. These tests, described in section 4a, minimized the within-cluster variances and maximized the between-cluster variances (Boyce 1996; Cheng and Lam 2000). In addition to a calendar of daily weather types created by the clustering procedure, the average values

TABLE 1. Meteorological predictors used in stepwise logistic regression for Ottawa.

Predictor	Description
V001-048	Hourly surface and 6-hourly upper-air wind direction indices
V049-072	6-hourly temperature difference between upper air and surface
V073-096	Hourly total cloud cover
V097-120	6-hourly vertical velocity (Ω) at six atmospheric levels*
V121-168	Surface and upper-air 6-h temperature changes
V169-172	6-h sea level air pressure changes
V173-196	6-h geopotential height changes at six atmospheric levels
V197-244	Surface and upper-air 6-h dewpoint depression changes
V245-248	6-hourly difference between max temperature at six atmospheric levels and surface temperature
V249-252	6-hourly area between the temperature profile with $>0°$C and the 0°C isotherm is the warm layer aloft
V253-256	6-hourly height of top of the warm layer with respect to temperature
V257-260	6-hourly area between the temperature profile with $<0°$C and the 0°C isotherm in the cold layer above the surface
V261-264	6-hourly height of top of the cold layer with respect to temperature
V265-280	Same as V249-264 except using dewpoint temperature
V281-304	Hourly sea level air pressure
V305-328	6-hourly temperature advection at six atmospheric levels
V329-352	6-hourly geopotential height at six atmospheric levels

* The six atmospheric levels are 1000, 925, 850, 700, 600, and 500 hPa.

and standard deviations were calculated for the various meteorological variables for all days within each type.

b. *Identification of the weather types most highly associated with freezing rain events*

The occurrence of freezing rain was used in the identification of the synoptic types that are most highly associated with those events. The occurrence frequency of freezing rain for each type was then determined to ascertain whether the frequency of freezing rain within a particular type was distinctively high or low. In addition, a ratio of the type's association with freezing rain events (actual frequency) to the occurrence of the type in the entire record (expected frequency) was utilized to determine whether any of the categories were overrepresented for freezing rain events. Types with ratios significantly greater than 1.0 had a greater proportion of days with freezing rain events than would be expected based on the frequency of the weather type. The statistical χ^2 test was employed to determine whether or not the theoretical frequency among the freezing rain events was significantly higher than the expected frequency. This method was then applied to specific hourly categories, such as $\geq$1, $\geq$4, and $\geq$6 h, representing the number of hours when freezing rain was observed during a day (0000–2300 LST).

c. *Development of the freezing rain prediction model*

Although the weather conditions for each day within a weather type are most similar to each other, there still exists some degree of within-category variance. Furthermore, not all days within an identified freezing rain type possess freezing rain events. Therefore, the day-to-day variation of weather conditions within an identified category could be important to the occurrence or nonoccurrence of freezing rain. A stepwise logistic regression procedure was performed on all days within the identified weather types most highly associated with freezing rain to determine which meteorological factors were the most significant in contributing to freezing rain events. The logistic regression procedure was the preferred prediction model for this study since the measurement data represented a dichotomous variable (taking the value of either 1 or 0 for occurrence or nonoccurrence of freezing rain) (Chap 1998; Allison 1999). As well, the output from this regression procedure, in the form of probability of freezing rain occurrence, was easy to interpret.

Predictors used in the regression procedure, which were derived from hourly surface observations and 6-hourly upper-air reanalysis data, are described in Table 1. In order to avoid multicollinearity, the hourly surface temperatures alone were not used as predictors since they were used to derive other variables. The predictors were straightforward, with the exception of some of the derived predictors that are described in the following sections. A wind direction index (WDI) was used in the regression analysis since the wind direction angle is discontinuous at 360°. The WDI is defined differently for the surface and upper-air winds since predominant wind directions tend to be different between the surface and upper level under freezing rain conditions. The surface WDI was defined as follows:

$$\mathrm{WDI} = 1 + \sin(\theta), \tag{2}$$

where θ is the wind direction expressed in radians. This index ensured that the WDI attains its maximum value of 2 when the surface wind is from the east, and its minimum value of 0 when the surface wind is from the west. These values corresponded to the maximum and minimum occurrence frequency of freezing rain events in Ottawa, respectively. For upper-air winds, the WDI was modified as follows:

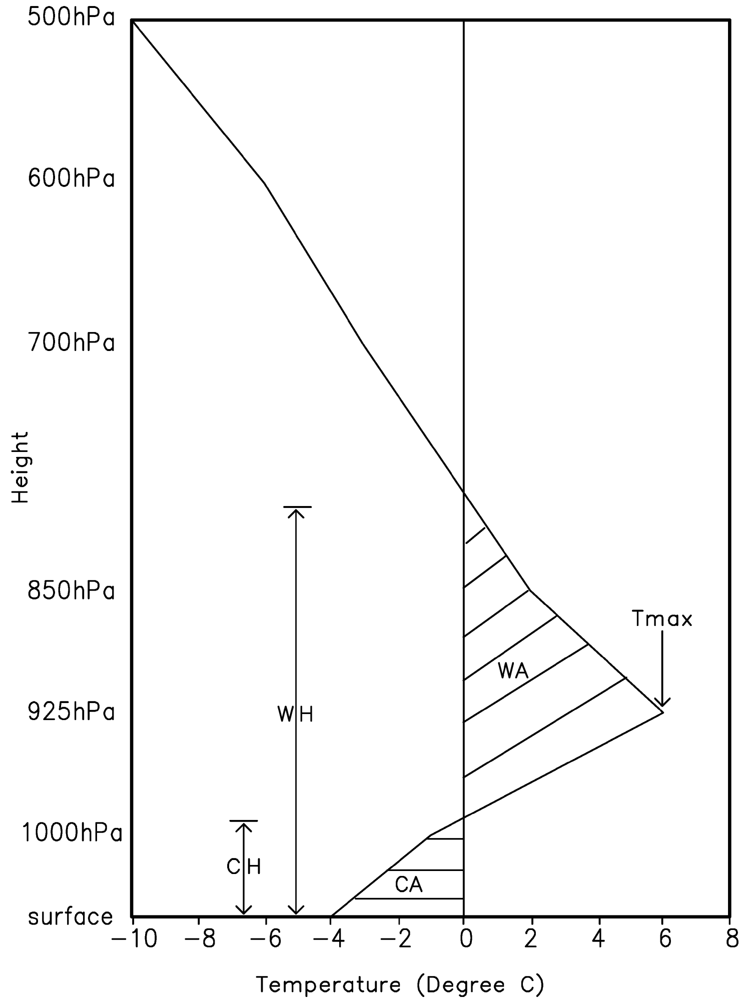

FIG. 1. Schematic illustration of the warm- and cold-layer variables. (Tmax refers to the maximum temperature at six upper atmospheric levels; WA and CA are, respectively, the areas of the warm and cold layers above the ground; WH and CH indicate the heights of the top of the warm layer and the cold layer, respectively, with respect to temperature.)

$$\mathrm{WDI} = 1 - \sin\left(\theta + \frac{\pi}{4}\right). \tag{3}$$

In this case, the WDI reached its maximum value when the upper winds were from the southwest and its minimum value when the upper winds were from the northeast, coinciding with the maximum and minimum occurrence frequency of freezing rain events in Ottawa.

Warm- and cold-layer variables were also used in the stepwise logistic regression and measured in temperature–height coordinates over the depth of the layer (Fig. 1). A variable termed the warm area (WA) was defined as the area between the 0°C axis and the portion of the temperature profile that is greater than 0°C aloft and measured in meter degrees Celsius (predictors V249-252 in Table 1). Similarly the cold area (CA) was defined as the area between the 0°C axis and the temperature profile that is less than 0°C near the surface (V257-260). The heights of the warm- and cold-layer tops (WH and CH, respectively) are measured in meters above ground level (V253-256 and V261-264). When required, a linear interpolation with respect to height was used to determine the warm- and cold-layer variables. The dewpoint temperature areas and heights (V265-280 in Table 1) were derived using a similar method. Another set of the variables (V245-248) represented the difference between the maximum temperature at the six upper levels and the surface temperature in degrees Celsius. All of these warm- and cold-layer variables were only calculated when the warm and cold layers were present (i.e., the temperature profile must possess a value >0°C aloft and ≤ 0°C near the surface); otherwise, they were set to zero.

The logistic regression methodology used a model that followed the method of maximum likelihood, which is a popular and widely used method of estimation for a variety of statistical models (Allison 1999). Accordingly, the dependent variable was set to 1 when freezing rain occurred on at least one hourly observation during a day; otherwise, it was set to 0. The stepwise logistic regression was then employed for all days, excluding days when each of the 24 hourly observed surface temperatures were >0°C (see section 4 for details), within the identified weather types most highly associated with freezing rain events. For k explanatory variables and $i = 1, \ldots, n$ individual cases, the logistic equation for predicting the likelihood of freezing rain events was given by

$$p_i = \frac{e^{\alpha+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_k x_{ik}}}{1 + e^{\alpha+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_k x_{ik}}}, \qquad (4)$$

where p_i is the probability of freezing rain occurrence; x is a predictor; and a and β are parameters of the model.

d. *Validation of the model*

The developed model was verified for the independent or validation dataset during the winter seasons (November–April) from 1991/92 to 2000/01. The evaluation was divided into two steps: 1) weather-type verification and 2) logistic regression model verification. For weather-type verification, component scores for each day of the validation dataset were determined by multiplying the post-eigenvector matrix (using data from 1958 to 1991) by validation data matrix. The new component scores were used to compare with the original scores since both used the same eigenvector matrix. Based on the new component scores, discriminant function analysis was used to assign each of all days within the validation dataset into one of the predetermined weather types using the centroids of the weather types as seeds. Since the weather types and their respective characteristics have already been predetermined, discriminant analysis is an appropriate tool to assign each day of the validation dataset into one of the predetermined weather types (Klecka 1980; Lam and Cheng 1998).

Following determination of the weather type for each day of the validation dataset, a within-category logistic regression algorithm from the developed model was used to predict the probability of freezing rain occurrence within the weather types that were most highly associated with freezing rain. These results were then compared with actual freezing rain observations within the validation dataset to assess the validity of the prediction model.

4. Results and discussions

a. *Developmental dataset: Identification of synoptic types associated with freezing rain*

The PCA was applied to the 240 weather variables for all days within the winter season from 1958/59 to 1990/91, producing an 18-component solution that explained 92% of the total variance within the developmental dataset. The remainder of the components with resulting eigenvalues less than one were discarded. The thermodynamic variables (air temperature and dewpoint) were found to be the main contributors to component 1, explaining over 36% of the total variance. Sea level pressure, total cloud cover, and south–north wind velocity aloft also contributed to component 1. The loadings for component 2, explaining an additional 17% of the total variance, were dominated by west–east wind velocity and sea level pressure. Component 3, explaining over 10% of the variance, was largely dominated by south–north surface wind velocity and winds aloft. Component 4, explaining nearly 10% of the variance, was largely determined by sea level pressure and total cloud cover. The remaining components 5–18 explained nearly 20% of the total variance and were largely comprised of terms that describe the diurnal changes of the variables.

The average linkage clustering procedure was employed to derive clusters possessing similar large-scale synoptic characteristics in terms of the daily 18-component scores. Determination of the cluster number to retain was achieved through a variety of statistical tests that included the semipartial R^2, pseudo-F, pseudo-t^2, and explained variance R^2. The semipartial R^2 is the ratio of the increased within-cluster variance after joining two clusters to the variance for the entire dataset. The pseudo-F is the ratio of between-cluster to within-cluster variances. The pseudo-t^2 is the ratio of the increased within-category variance after joining two clusters to the variance within each of two clusters (SAS Institute Inc. 1999; Eder et al. 1994). The number of weather types for retention in the model is determined by observing the largest decrease in R^2, the largest increase in both the semipartial R^2 and pseudo-t^2, after joining two clusters, and a local maximum in the pseudo-F.

Using the above procedures, 13 major synoptic weather types were identified for Ottawa for all days within the winter season of 1958/59–1990/91 based on differences in their meteorological characteristics. Table 2 shows the within-weather-type mean values of the meteorological variables at 1200 UTC. Based on weather observations from 1953 to 2000, freezing rain had the highest frequency of occurrence at 1200 UTC, compared to the other hours (0600, 1800, and 0000 UTC) when the NCEP–NCAR reanalysis data were available. These 13 major synoptic weather types represented 85% of the total number of days during the period. The smaller synoptic weather types, which made up the remaining 15% of the days, were removed from the analysis. These smaller types were largely made up of days that either had no freezing rain occurrence or freezing rain events involving 1 h during a day. However, freezing rain events with synoptic types outside of the 1–4 range were still included in the analysis evaluating prediction model robustness (see section 4c for details). During short-

TABLE 2. Mean values of meteorological variables at 1200 UTC for weather types at Ottawa (developmental dataset: Nov–Apr 1958/59–1990–91; the standard deviations are in parentheses).

Type	Days (% frequency)	Surface T_a (°C)[a]	Surface T_d (°C)[b]	Surface Pressure (hPa)	Surface U wind[c] (m s^{-1})	Surface V wind[d] (m s^{-1})	Surface Cloud cover (tenths)	700 hPa T_a (°C)[a]	700 hPa T_d (°C)[b]	700 hPa U wind[c] (m s^{-1})	700 hPa V wind[d] (m s^{-1})
1	336 (5.51)	−3.9 (3.6)	−6.1 (4.1)	1005.7 (6.4)	−1.7 (3.7)	−0.5 (2.4)	9.8 (0.5)	−13.1 (5.3)	−16.0 (5.8)	16.1 (6.0)	13.8 (5.1)
2	786 (12.90)	−3.2 (4.5)	−6.0 (5.0)	1017.6 (7.5)	−2.9 (2.7)	−0.3 (1.7)	9.2 (1.8)	−7.4 (4.4)	−14.9 (6.7)	12.5 (5.9)	3.6 (6.2)
3	356 (5.84)	−5.2 (3.5)	−8.9 (3.9)	1017.6 (6.9)	−5.0 (2.9)	−2.2 (1.7)	9.1 (1.9)	−10.4 (3.6)	−17.8 (5.6)	1.9 (7.7)	4.0 (5.3)
4	438 (7.19)	5.4 (4.8)	2.4 (4.8)	1009.7 (9.3)	−1.3 (3.3)	1.6 (2.3)	8.2 (3.0)	−3.2 (3.8)	−9.7 (6.4)	13.0 (7.2)	8.5 (9.3)
5	309 (5.07)	−4.5 (4.4)	−8.3 (4.7)	1007.1 (7.2)	5.2 (2.6)	−2.8 (2.7)	8.1 (2.8)	−15.2 (3.5)	−20.7 (4.9)	7.7 (6.9)	−9.6 (6.0)
6	426 (6.99)	−2.1 (4.6)	−7.0 (4.2)	1022.2 (6.1)	1.5 (1.9)	−1.3 (2.1)	3.0 (3.3)	−10.6 (4.1)	−24.2 (5.9)	7.0 (6.6)	−9.2 (5.9)
7	456 (7.48)	−1.2 (3.5)	−4.0 (3.9)	1010.1 (7.1)	2.1 (2.3)	2.0 (2.3)	8.4 (2.7)	−12.8 (4.3)	−19.9 (5.7)	16.0 (6.9)	1.3 (6.8)
8	370 (6.07)	−9.1 (4.2)	−12.5 (4.2)	1017.7 (6.8)	1.3 (2.4)	1.6 (2.3)	7.5 (3.2)	−17.5 (5.3)	−24.9 (6.0)	17.7 (5.5)	−0.9 (6.1)
9	217 (3.56)	4.8 (3.9)	2.1 (3.9)	1013.5 (5.7)	1.9 (2.3)	0.1 (2.4)	8.6 (2.5)	−6.0 (3.6)	−15.0 (6.9)	16.6 (6.8)	−0.6 (6.2)
10	391 (6.42)	−18.1 (4.0)	−22.6 (4.7)	1020.0 (8.2)	2.4 (2.5)	−0.3 (1.9)	4.0 (3.7)	−23.4 (4.6)	−31.5 (4.8)	15.1 (6.2)	−6.0 (6.8)
11	451 (7.40)	−9.2 (5.0)	−13.7 (5.1)	1023.0 (5.9)	2.3 (2.3)	−2.4 (2.2)	4.4 (3.7)	−15.7 (4.3)	−26.3 (5.5)	9.0 (8.1)	−8.5 (6.3)
12	295 (4.84)	−21.8 (4.4)	−27.3 (4.7)	1027.5 (7.3)	3.1 (2.6)	−2.5 (2.4)	1.5 (2.3)	−23.7 (4.5)	−34.4 (5.3)	11.8 (6.8)	−11.4 (6.1)
13	336 (5.51)	−15.0 (3.4)	−18.8 (4.2)	1014.9 (6.5)	−3.3 (2.5)	−0.8 (1.7)	9.0 (2.0)	−16.2 (4.2)	−21.0 (5.5)	12.2 (5.9)	4.3 (5.1)

[a] Air temperature.
[b] Dewpoint temperature.
[c] Positive value is for westerly wind.
[d] Positive value is for southerly wind.

duration events, there are considerable uncertainties in determining whether freezing rain has actually occurred. This is especially true when surface temperatures are very close to the melting point. As an illustration, during the period 1958/59–1990/91, 31% of the total cases with 1-h-duration freezing rain were associated with a surface temperature ranging between $-0.6°$ and 0.6°C, while only 11% of the events with duration $\geq$6 h occurred within this same temperature range. Other sources of uncertainty in observing these short-duration freezing rain events include

- Drop size: freezing precipitation drop size diameter may be close to the rain/drizzle threshold of 0.5 mm, in which case, freezing rain may in fact be observed as freezing drizzle (Environment Canada 1996, chapter 3).
- Location of icing sensor: the icing sensor may not be collocated with the temperature probe.
- Human error: the shorter the freezing rain event, the greater the likelihood that the freezing rain may not be detected by a weather observer, either because he/she was not outside when it occurred, or the observer noticed rain but not the fact that it was freezing.

Since each of the weather types displays a distinctive air mass and synoptic signature, a specific regime of freezing rain should be related to each. The study indicated that the number of freezing rain days varied considerably among the synoptic types. While some weather types had no days with freezing rain occurrence, others were comprised of many days with freezing rain events. For example, more than half of the freezing rain days were observed in weather type 2, capturing 164, 78, and 39 days with freezing rain events occurring $\geq$1, $\geq$4, and $\geq$6 h during a day, respectively (Table 3).

To identify the synoptic types most highly associated with freezing rain events, a category frequency ratio was calculated. This ratio compares the percentage frequency of days with freezing rain events (actual frequency) to the percentage frequency of the weather type within the entire record (expected frequency). The resulting ratios are provided in Table 3. For example, for synoptic type 2 the expected frequency of freezing rain events should be approximately 13%, based on the expected frequency of the weather type within the entire record. However, the actual frequency of freezing rain events occurring at least 1 h during a day is closer to 50%, or about 4 times what might otherwise be expected. A χ^2 test was employed to ascertain whether the observed frequencies of freezing rain cases were significantly different from their expected occurrences (χ^2-test significance level of 0.001). If a weather type possessed a reasonable number of freezing rain cases (i.e., greater than the number of the cases within each of the remaining nonfreezing rain weather types) and the frequency ratio was $>$1.0, it was selected as a freezing rain–related weather type. Based on these two criteria, four synoptic types (1–4) were identified over the

TABLE 3. Within-synoptic-type frequency of freezing rain at Ottawa (developmental dataset: Nov–Apr 1958/59–1990/91). Note that bold and italic data indicate the weather types most highly associated with freezing rain events.

Synoptic type			Freezing rain events ≥1 h			≥4 h			≥6 h		
Type	Days	Frequency (%)[a] (a)	Days	Frequency (%)[b] (b)	Ratio[c] (b)/(a)	Days	Frequency (%)[b] (c)	Ratio[c] (c)/(a)	Days	Frequency (%)[b] (d)	Ratio[c] (d)/(a)
1	***336***	***5.51***	***25***	***7.60***	***1.38***	***4***	***3.10***	***0.56***	***3***	***4.55***	***0.82***
2	***786***	***12.90***	***164***	***49.85***	***3.86***	***78***	***60.47***	***4.69***	***39***	***59.09***	***4.58***
3	***356***	***5.84***	***38***	***11.55***	***1.98***	***18***	***13.95***	***2.39***	***12***	***18.18***	***3.11***
4	***438***	***7.19***	***40***	***12.16***	***1.69***	***16***	***12.40***	***1.73***	***10***	***15.15***	***2.11***
Subtotal[d]	**1916**	**31.45**	**267**	**81.16**	**2.58**	**116**	**89.92**	**2.86**	**64**	**96.97**	**3.08**
5	309	5.07	4	1.22	0.24	0	0.00	0.00	0	0.00	0.00
6	426	6.99	2	0.61	0.09	0	0.00	0.00	0	0.00	0.00
7	456	7.48	8	2.43	0.32	0	0.00	0.00	0	0.00	0.00
8	370	6.07	1	0.30	0.05	0	0.00	0.00	0	0.00	0.00
9	217	3.56	6	1.82	0.51	3	2.33	0.65	1	1.52	0.43
10	391	6.42	0	0.00	0.00	0	0.00	0.00	0	0.00	0.00
11	451	7.40	3	0.91	0.12	0	0.00	0.00	0	0.00	0.00
12	295	4.84	0	0.00	0.00	0	0.00	0.00	0	0.00	0.00
13	336	5.51	8	2.43	0.44	1	0.78	0.14	1	1.52	0.27
Total[e]	5167	84.80	299	90.88		120	93.02		66	100.00	

[a] Represents percentage frequency of the weather type.
[b] Represents percentage frequency of the days with 1, 4, or 6 h or more freezing rain events within a particular weather type.
[c] Ratio of percentage frequency of the days with freezing rain events over the percentage frequency of the weather type. A number greater than one indicates that a larger proportion of days in the weather type possess freezing rain events than would be expected based only on the frequency of the weather type.
[d] Represents the sum of the four weather types identified as being most highly associated with freezing rain events.
[e] Represents the sum of the 13 weather types.

33-yr period as the primary freezing rain weather types. These weather types accounted for 81%, 90%, and 97% of the freezing rain events lasting greater than or equal to 1, 4, and 6 h during a day, respectively, at Ottawa International Airport.

b. *Developmental dataset: Results from stepwise logistic regression*

There exists some degree of within-category variance in the development dataset, even though the weather situations for each day within a weather type are similar to each other. For example, some days within the four freezing rain–related weather types, particularly weather type 4, exhibited relatively warm mean meteorological characteristics (specifically surface temperatures >0°C), which would not normally be expected to produce freezing precipitation. A day was excluded from the development of the regression model if each of the 24 hourly observed surface air temperatures was greater than 0°C. Using this approach, 636 days were excluded from the analysis in total. No days in weather type 1 met this screening criterion while 146, 160, and 330 days were found for weather types 2, 3, and 4, respectively. It is interesting to note that, of the days removed, only one day had a freezing rain event (2 hourly observations).

A stepwise logistic regression procedure was performed on all days within the four freezing rain weather types. The data sample used in the regression consisted of 1280 days, of which 266 days experienced freezing rain events occurring 1 h or more during a day. Table 4 lists the freezing rain predictors that were identified in the stepwise logistic regression model with an entry and retention significance level of 0.05. The regression results are summarized as follows:

1) There is a significant correlation between the occurrence of freezing rain events and the model predictions, with a concordance of 91.5%. Concordance is a measure of the model performance and is commonly used for logistic regression [the model R^2, judging the overall fit of a multiple regression model, is not suitable for binary data analysis (Chap 1998; Chatterjee et al. 2000)]. There are 818 560 different ways to pair the total number of 1280 days for weather types 1–4 without pairing a day with itself. Of the pairs, 548 836 are matched, having days with either both 1s (266 days) or both 0s (1014 days) for freezing rain occurrence. The remaining mismatched pairs (269 724) occur when one day has a 1 (occurrence of freezing rain) and another day has a 0 (nonoccurrence of freezing rain), and are actually used to measure the concordance. For each of the mismatched pairs, if the day with a 1 has a higher probability value predicted than another day with a 0, that pair is concordant; otherwise, the pair is discordant (Allison 1999). The measure of concordance varies between 0 and 1, with large values referring to stronger relationships between observed freezing rain occurrences and the model predictions. As a

TABLE 4. Freezing rain predictors identified from the logistic regression model at the 0.05 significance level (concordant: 91.5%) for Ottawa. The developmental sample consisted of hourly surface observations and 6-hourly NCEP–NCAR reanalysis data for the winter seasons (Nov–Apr) of 1958/59–1990/91. The time (UTC) and pressure level of the predictors are shown in parentheses.

Freezing rain predictors	Estimate	Pr > chi square
Intercept	−3.3337	<0.0001
Surface wind direction index (0500)	0.6424	0.0002
Upper-air wind direction index (700 hPa/0000)	1.5358	<0.0001
ΔT ($T_{\text{upper air}} - T_{\text{surface}}$) (850 hPa/1800)	0.1600	0.0033
ΔT ($T_{\text{upper air}} - T_{\text{surface}}$) (700 hPa/0600)	0.1841	0.0074
ΔT ($T_{\text{upper air}} - T_{\text{surface}}$) (700 hPa/0000)	0.1931	<0.0001
ΔT ($T_{\text{upper air maximum}} - T_{\text{surface}}$) (0000)	0.2422	0.0041
Sea level air pressure (0800)	−0.0014	0.0012
Sea level air pressure (0000)	−0.0008	0.0123
Total cloud cover (1600)	0.1495	<0.0001
Height of top of the warm layer with respect to dewpoint (0600)	0.5985	0.0299
Vertical velocity − omega (500 hPa/0600)	−0.5687	0.0007
Vertical velocity − omega (850 hPa/1200)	−1.3271	<0.0001
Vertical velocity − omega (925 hPa/1800)	−0.8222	0.0010
Surface temperature change in the past 6 h (1800)	−0.3560	<0.0001
Sea level air pressure change in the past 6 h (0600)	−0.2354	<0.0001
Upper-air temperature change in the past 6 h (500 hPa/1200)	0.2421	0.0003
Upper-air temperature change in the past 6 h (1000 hPa/1800)	0.1309	0.0128
Upper-air temperature change in the past 6 h (700 hPa/0000)	0.1655	0.0148
Surface dewpoint depression change in the past 6 h (1200)	−0.2291	0.0004
Upper-air dewpoint depression change in the past 6 h (700 hPa/1200)	−0.0693	0.0002
Upper-air dewpoint depression change in the past 6 h (700 hPa/1800)	−0.0782	0.0042
Upper-air dewpoint depression change in the past 6 h (700 hPa/0000)	−0.1211	0.0438
Upper-air dewpoint depression change in the past 6 h (925 hPa/0000)	−0.0744	0.0100
Temperature advection (850 hPa/1200)	0.6304	0.0273

result, 91.5% of the total mismatched pairs (269 724) produced from this logistic regression model possess a day where the occurrence of freezing rain has a higher predicted probability value than another day with no freezing rain.

2) The logistic regression model identified freezing rain predictors at Ottawa that included wind direction indices, temperature differences between the upper air and surface, 6-h temperature changes, and warm air advection. These predictors are consistent with the physical processes typically associated with freezing rain events. From the predictor information provided in Table 4, based on the logistic regression model results, we can define the weather conditions associated with a high probability of freezing rain occurrence at Ottawa International Airport. These include easterly–northeasterly surface winds and southwesterly winds at midatmospheric levels, the presence of a temperature inversion in the low to midatmospheric levels with an associated air temperature >0°C aloft and ≤0°C at the surface, falling sea level air pressure, high total cloud cover, increasing air temperatures aloft (i.e., warm air advection at midatmospheric levels), surface temperatures decreasing in the past 6 h, and dewpoint depression decreasing in the past 6 h (i.e., increasing moisture), both at the surface and midatmospheric levels. These results corroborated the results in previous studies (Bocchieri 1980; Huffman and Norman 1988; Rauber et al. 2000).

When attempting to use multiple regression to develop a model, it is important to consider multicollinearity among the explanatory variables. Variance inflation factors (VIFs) can be used to identify multicollinearity. High VIFs indicate that two or more collinear independent variables are included in the model (Draper and Smith 1998). Chatterjee et al. (2000) suggested that a VIF in excess of 10 is an indication that multicollinearity may be causing problems in estimation. No strong collinear relationships existed within the explanatory predictors in this model since the VIF value of each predictor was less than 2 (Draper and Smith 1998; Lawrence and Arthur 1990; SAS Institute Inc. 1999). The largest VIF value of any of the predictors used in the model was 1.72, indicating that the largest multiple coefficient of determination (R^2) was 0.42 among the model explanatory predictors [VIF = $(1 - R^2)^{-1}$].

Table 5 shows the results of the logistic regression model in terms of logistic regression probability. It is important to determine a cutoff logistic regression probability for prediction of freezing rain events. For this study, a probability of 0.6 was selected as the cutoff threshold, corresponding to the probability where the number of freezing rain cases correctly forecast by the model was higher than the false alarms. If a lower cutoff probability was used, the model would produce much higher false alarm rates. Using this probability threshold, the model was able to correctly identify 154 freezing rain cases lasting ≥1 h during a day, while yielding only 28 false alarms, resulting in a postagreement of

TABLE 5. Breakdown by logistic regression probability for freezing rain events within weather types 1–4 at Ottawa (developmental dataset: Nov–Apr 1958/59–1990/91). Note that bold and italic data indicate that threshold of logistic probability (≥0.6) can be used for prediction of freezing rain. The last row represents the percentage of the total freezing rain events that can be identified by the model using 0.6 as the logistic probability cutoff.

Logistic probability	Days without freezing rain			Days with freezing rain events				
	No precipitation	Snow/rain	Freezing drizzle	≥1 h	≥2 h	≥4 h	≥6 h	≥8 h
≥0.9	***0***	***1***	***2***	***71***	***66***	***48***	***32***	***19***
0.8–0.9	***0***	***1***	***0***	***34***	***29***	***19***	***10***	***6***
0.7–0.8	***2***	***6***	***1***	***21***	***16***	***9***	***6***	***3***
0.6–0.7	***1***	***11***	***3***	***28***	***21***	***12***	***6***	***3***
0.5–0.6	1	8	4	9	6	2	0	0
0.4–0.5	5	15	6	21	17	5	2	1
0.3–0.4	4	28	2	15	12	7	3	1
0.2–0.3	11	46	5	21	17	5	2	0
0.1–0.2	31	76	18	25	17	5	0	0
0.01–0.1	193	284	31	18	11	3	2	1
<0.01	121	91	6	3	1	1	1	1
FAR* (≥0.6)		***← 15% →***						
POD (≥0.6)**				***58%***	***62%***	***76%***	***84%***	***89%***

* FAR: false alarm rate. The ratio is [1 − postagreement (PA)], where PA represents the number of correct predictions divided by the total number of predictions for freezing rain events, with a perfect PA equal to 1 (or 100%).

** POD: probability of detection represents the number of correct forecasts divided by the number observed in a category. Perfect probability of detection = 1 (or 100%).

85% and a false alarm rate (FAR) of 15% for freezing rain events. The corresponding postagreement and FAR associated with a cutoff probability of 0.8 were 96% and 4%, respectively. Postagreement represents the number of correct predictions divided by the total number of predictions for freezing rain events, with a perfect postagreement equal to 1 (or 100%). The FAR is defined as (1 − postagreement) (Stanski et al. 1989). Of the 28 false alarms, snowfall/rainfall and freezing drizzle were observed on 19 and 6 days, respectively (Table 5). Of the 369 days with no observed precipitation used in logistic regression analysis, only 3 days were incorrectly identified as freezing rain events with logistic probability ≥0.6.

It is noteworthy that this model may be particularly well suited for prediction of the occurrence of freezing rain events lasting several hours in duration. For example, the probability of detection (POD) resulting from the model was 58% for freezing rain events lasting ≥1 h during a day, but 89% for freezing rain events lasting ≥8 h during a day (Table 5). POD is defined as the number of correct forecasts divided by the total number of observed in that category, with a perfect POD equal to 1 (or 100%) (Stanski et al. 1989).

There are three factors that may have contributed to the shortfall in identifying some shorter-duration freezing rain events. One factor is based on the limited temporal resolution of the NCEP–NCAR reanalysis data (every 6 h), which may contribute to difficulties in predicting events shorter than the temporal resolution of the data. The other two factors are related to limitations in the spatial and vertical resolution of the NCEP–NCAR reanalysis data. These resolution limitations likely contributed to short-duration freezing rain events sometimes being observed when reanalysis data identified a minimal warm layer aloft. A warm layer aloft is defined in this study as a layer warmer than 0°C extending above a surface-based layer of air colder than 0°C. In most of the short-duration events, a mix of precipitation types was reported (i.e., snow, ice pellets, freezing drizzle), indicating the presence of a vertical temperature profile with either a minimal or nonexistent warm layer aloft. For example, there were a total of 53 days with a 1-h occurrence of freezing rain for the period 1958/59–1990/91; 31 of these events were essentially missed by the model where the predicted probability was <0.6. Examining the NCEP–NCAR daily vertical pressure level temperature profiles for four times daily on each of these 31 days, it was determined that 17 days or 55% had no warm layer aloft during any of the four reanalysis hours. Of the remaining 22 days with a 1 h occurrence of freezing rain specified with a high probability (≥0.6), only 4 days or 18% were identified without a warm layer during any of the 4 h. In fact, about 31% of freezing rain days in the developmental dataset had no warm layer, as determined from the NCEP–NCAR profiles, and only about 13% of these events can be identified by the model with the probability ≥0.6.

To investigate the relative frequency of ‘‘nonclassical’’ freezing rain events (i.e., freezing rain occurring in the absence of a warm layer aloft), radiosonde, surface-observed, and reanalysis data for the period 1971–92 at Maniwaki, Quebec (about 120 km north of Ottawa), were analyzed. Since the sounding data were only available twice per day at 0000 and 1200 UTC, the vertical temperature profiles resulting from the reanalysis data were examined for these same times. Using this approach, the percentages of nonclassical freezing rain cases at both 0000 and 1200 UTC were 26% and 38% for the observed sounding and reanalysis data, respectively. If we use a slightly less restrictive surface temperature threshold to define a warm layer (by modifying the surface temperature threshold from 0° to 1°C), the corresponding percentages were 15% and 36% for the sounding and reanalysis data, respectively. Given the relatively poor temporal resolution of the sounding data, this less restrictive threshold seems justified to capture instances in which the warm layer aloft has reached the surface (at the time of the radiosonde observation), shortly after the end of a freezing rain event. In order to effectively compare results between Ottawa and Maniwaki, a similar analysis was conducted for Ottawa based on vertical reanalysis temperature profiles at 0000 and 1200 UTC. In this case, about 21% of the total freezing rain cases at Ottawa were associated with the nonclassical formation process. As above, when the surface temperature threshold used to define the warm layer was changed to 1°C, the percentage of freezing rain cases remained the same. The Ottawa results are quite similar to those for Maniwaki (recall that the percentage of freezing rain cases without the warm layer resulting from reanalysis data for Maniwaki only changed 2% when the surface temperature threshold changed). When comparing reanalysis data, it is worth noting that the percentage of freezing rain days with a warm layer aloft at Ottawa is higher than that at Maniwaki (79% versus 62%) because of the differences in topography between the two sites. In fact the average seasonal total number of freezing rain days at Ottawa is almost three times higher than at Maniwaki.

c. Robustness of the freezing rain prediction model

In this section, the robustness of the developed freezing rain prediction model is examined using stepwise logistic regression for the different datasets: 1) PCA scores were used instead of the original weather predictors, 2) without synoptic typing, all days were used except those with each of the 24 hourly observed surface air temperatures >0°C, and 3) all days within weather types 1–4 were used, including days with surface hourly temperatures >0°C. Comparing the results from these tests with the original model, it was determined that the original model performed best as described below.

A recent study (Applequist et al. 2002) compared five different linear and nonlinear statistical methodologies (linear regression, discriminant analysis, logistic regression, neural networks, and a classifier system) for probabilistic quantitative precipitation forecasting. The results indicated that logistic regression using PCA scores performed best among all methodologies. In order to ascertain whether PCA scores could serve as a better predictor set than the original weather variables for freezing rain prediction, the correlation-matrix-based PCA scores were calculated from the same potential predictors used in the earlier logistic regression model (as shown in Table 1). The stepwise logistic regression approach determined that 18 out of the 45 leading principal components were most significant in contributing to freezing rain events. The paradigm based on the relative operating characteristic (ROC), a graphical display of the relationship between hit and false alarm rates as decision criterion varies, is suitable to effectively compare results between both models (Mason 1982; Stanski et al. 1989; Wilks 1995). It is clearly shown in Fig. 2a that logistic regression using PCA scores was not able to provide a better solution than the use of original predictors. For example, although the number of false alarms, using the cutoff probability of 0.6, was the same for both models, the number of hits resulting from the original model was 22% greater. However, an advantage for using PCA scores as predictors is that all predictors are orthogonal without multicollinearity.

This study applied both synoptic typing and logistic regression together for freezing rain prediction. In order to determine whether it was necessary to perform synoptic typing prior to the application of a regression model, the logistic regression model was redeveloped using all days with the surface temperature ≤0°C for at least 1 h during a day (Fig. 2b, test model 2). To effectively compare results between the test and original models, the original model was used to calculate logistic probability for days that were previously excluded from the original model. Figure 2b shows that at a given false alarm rate, the POD from the original model is usually higher than from the test model. For example, the numbers of hits and false alarms for a cutoff probability of 0.6 were over 3% less and 14% greater than the original model results, respectively, since several predictors were changed in the test model. Although the results from the model with weather typing were slightly better, it was still valuable to do synoptic typing prior to using the logistic regression model for several reasons. Within-synoptic-type regression can reduce some noise from the regression analysis by including all days (Nichols et al. 1995; Kalkstein et al. 1997; Cheng and Lam 2000), thus enhancing the statistical power of the methodology for prediction of freezing rain events. Over 40% of the total number of days (62) with freezing rain events that were not included in weather types 1–4 were almost evenly distributed in the prediction probability categories greater than 20% (e.g., >90%, 80%–90%, etc.) from the original and test models. This implied that both models were less able to identify these events as the majority of them were of a short duration with no warm layer aloft.

When the logistic regression was applied for all days within weather types 1–4 (including days with surface hourly temperatures >0°C) (Fig. 2c, test model 3) and the original model was used to calculate logistic probability for days that were not previously included in the original model, the results were slightly worse than

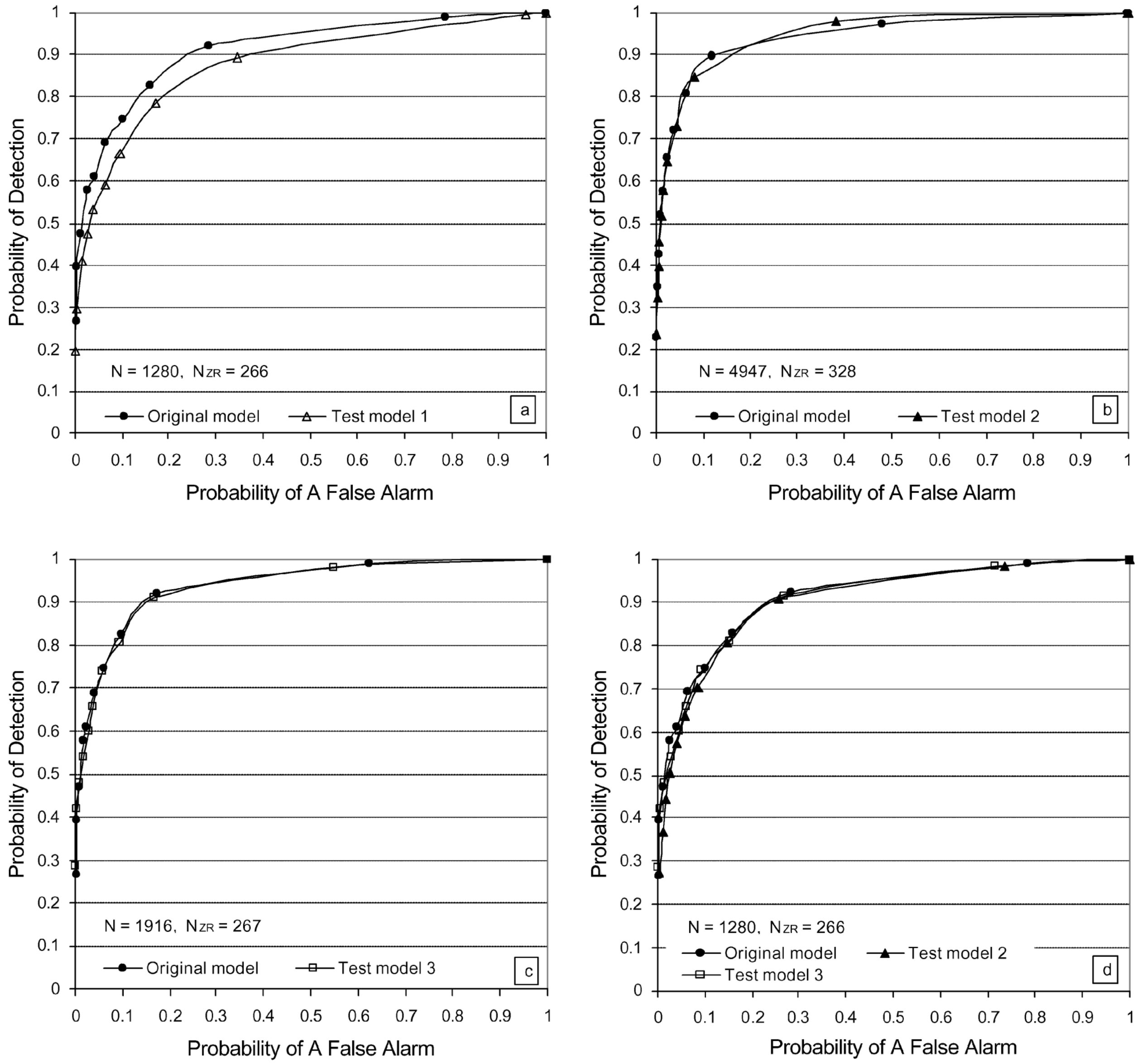

FIG. 2. ROCs between the original model and test models for freezing rain events lasting 1 h or more during a day in Ottawa (N = number of sample days; N_{ZR} = number of freezing rain events). Test models are (a) test model 1 using scores of principal components analysis; (b) test model 2 using all days with the surface temperature $\leq 0°C$ for at least 1 h during a day; (c) test model 3 using all days within weather types 1–4 including days with surface hourly temperatures $>0°C$; and (d) comparison between the original model and test models 2 and 3 using the same data sample on which the original model was developed.

those resulting from the original model (Fig. 2c). For example, the number of hits was reduced by 10 days compared to the original 154 days, while the false alarms increased by 1 day compared to the original result of 28 days.

From Figs. 2a–c, ROC curves in test model 2 seem to show the best performance among the three types of models. This is illustrated in Fig. 2b, with test model 2 lying closest to the upper left corner with the lowest probability of a false alarm and highest POD (Mason 1982; Stanski et al. 1989). It is noteworthy that this slight improvement was the result of improved detection in a large number of nonfreezing rain events rather than detection of freezing rain occurrences. The detection of nonfreezing rain events is less significant since nonfreezing rain events used in Fig. 2b account for 93.4% of the total sample days. Therefore, results of the models need to be compared using the same size of data sample. The ROC curves were plotted in Fig. 2d for the original model and test models 2 and 3 (Figs. 2b,c) using the same days that were used to develop the original model. The comparison shows that the original model performed slightly better than the test models, with PODs typically higher for a given false alarm ratio.

d. Validation of the model

In order to validate the model, discriminant function analysis was used to assign each day of the validation dataset (1991/92–2000/01) into one of the weather types predetermined from the developmental dataset (1958/59–1990/91). Within-type mean values of meteorological variables at 1200 UTC for the validation dataset are displayed in Table 6. This validation dataset yielded similar meteorological characteristics within synoptic types to those constructed from the developmental dataset (Table 2). The within-category frequency of freezing rain events for the validation dataset was also used to validate the weather-typing procedure (Table 7). Based on a comparison of Tables 3 and 7, the results showed that within-type percentage frequencies of freezing rain events for both the developmental and validation datasets were similar. These results implied that the discriminant function analysis performed well in identifying or predicting the weather types most highly associated with freezing rain events.

Following the determination of the weather type for each day within the validation dataset, the logistic regression algorithm was used to calculate the probability of freezing rain occurrence for each of the days within weather types 1–4 for the period 1991/92–2000/01 (Table 8). As was the case for the developmental dataset, a probability of 0.6 was selected as the cutoff threshold for the prediction of freezing rain. Of the 46 days in the validation dataset forecast to have a probability $\geq$0.6, freezing rain was observed on 35 days, or a postagreement of 76% with the remaining 11 days or 24% representing false alarms. Of the 35 freezing rain days correctly forecast by the model, 16 days received freezing rain events lasting between 2 to 5 h, while 17 of the days experienced events of duration $\geq$6 h. For the 11 false alarm events, freezing drizzle or snow/rain were observed for 5 and 2 days, respectively. Of the total 85 days in which precipitation was not observed, only 4 days were incorrectly identified as freezing rain events by the model when using a prediction probability $\geq$0.6. For freezing rain events lasting 8 h or more during a day, the model predicted 91% (POD) of the total freezing rain cases from the validation dataset. In general, these percentages were better than the results from the developmental dataset for longer-duration freezing rain events.

In addition to the ROC paradigm (see section 2c), an attributes diagram was used to evaluate the reliability of the freezing rain prediction model and indicate the frequency bias of various probability categories (Stanski et al. 1989; Wilks 1995). For each of the forecast probability deciles centered on 5%, 15%, etc., the frequency of occurrence of a freezing rain event of at least 1 h duration was calculated. The observed frequencies were then plotted against the set of forecast probability categories (Fig. 3). The diagonal line in Fig. 3 represents perfect model reliability. For example, if a probability

TABLE 6. Mean values of meteorological variables at 1200 UTC for weather types at Ottawa (validation dataset: Nov–Apr 1991/92–2000/01; the standard deviations are in parentheses).

		Surface						700 hPa			
Type	Days (% frequency)	T_a (°C)[a]	T_d (°C)[b]	Pressure (hPa)	U wind[c] (m s^{-1})	V wind[d] (m s^{-1})	Cloud cover (tenths)	T_a (°C)[a]	T_d (°C)[b]	U wind[c] (m s^{-1})	V wind[d] (m s^{-1})
1	110 (6.07)	−2.8 (3.8)	−5.2 (4.6)	1004.3 (8.6)	−1.3 (2.9)	−0.4 (2.4)	9.3 (1.6)	−11.1 (4.5)	−13.4 (5.8)	16.6 (6.4)	11.9 (8.9)
2	131 (7.23)	−2.6 (3.8)	−5.4 (4.0)	1019.3 (6.8)	−2.4 (2.1)	−0.7 (1.4)	9.3 (1.6)	−6.6 (3.9)	−15.1 (7.5)	13.2 (5.5)	2.3 (6.1)
3	142 (7.84)	−4.8 (3.6)	−8.9 (4.3)	1019.2 (7.1)	−4.3 (2.2)	−2.0 (1.5)	9.5 (1.5)	−9.7 (3.6)	−17.4 (7.8)	2.1 (6.6)	3.6 (5.8)
4	106 (5.85)	5.3 (4.0)	2.4 (4.6)	1010.5 (7.7)	−1.7 (2.6)	1.2 (2.0)	9.0 (2.1)	−2.5 (3.5)	−8.1 (5.8)	14.9 (6.0)	11.1 (8.5)
5	61 (3.37)	−3.8 (4.5)	−8.0 (4.3)	1008.6 (6.1)	5.5 (1.9)	−2.3 (2.0)	7.6 (3.1)	−14.1 (3.2)	−20.2 (5.2)	5.3 (6.7)	−11.4 (6.5)
6	134 (7.40)	−1.1 (4.2)	−7.2 (3.8)	1021.5 (6.6)	1.3 (1.8)	−1.3 (2.3)	1.6 (2.6)	−10.4 (4.7)	−26.3 (7.3)	6.1 (7.3)	−9.2 (6.5)
7	134 (7.40)	−0.8 (3.6)	−3.6 (3.7)	1012.4 (6.4)	1.8 (1.9)	1.6 (1.9)	8.2 (3.1)	−12.5 (3.9)	−20.0 (5.4)	16.1 (6.7)	−0.2 (6.2)
8	86 (4.75)	−9.8 (4.4)	−13.1 (5.0)	1019.8 (5.9)	0.7 (1.9)	1.6 (1.8)	7.3 (3.3)	−16.9 (4.7)	−26.3 (6.9)	18.2 (5.0)	−1.7 (6.6)
9	71 (3.92)	4.2 (4.2)	1.4 (4.7)	1014.5 (6.6)	1.7 (2.2)	0.2 (2.2)	8.2 (2.8)	−5.8 (3.4)	−15.6 (7.3)	17.6 (5.6)	−1.1 (6.8)
10	67 (3.70)	−18.2 (3.6)	−22.8 (4.0)	1020.5 (6.3)	1.9 (2.1)	−0.1 (1.7)	2.9 (3.5)	−23.9 (4.4)	−33.2 (5.5)	14.1 (5.5)	−6.9 (6.2)
11	128 (7.06)	−9.6 (4.1)	−13.8 (4.5)	1024.0 (6.5)	2.1 (2.1)	−1.9 (1.9)	3.3 (3.6)	−15.7 (5.0)	−28.4 (6.9)	8.5 (5.5)	−9.2 (6.4)
12	75 (4.14)	−21.2 (4.1)	−27.2 (4.4)	1028.0 (7.9)	3.1 (2.2)	−2.1 (1.9)	1.0 (1.9)	−22.8 (4.5)	−35.0 (6.2)	11.5 (6.3)	−11.2 (6.0)
13	140 (7.73)	−15.0 (4.2)	−19.2 (4.6)	1016.9 (9.4)	−3.1 (1.7)	−1.1 (1.1)	9.4 (1.6)	−15.1 (4.4)	−19.9 (5.3)	15.7 (5.9)	2.5 (7.1)

[a] Air temperature.
[b] Dewpoint temperature.
[c] Positive value is for westerly wind.
[d] Positive value is for southerly wind.

TABLE 7. Within-synoptic-type frequency of freezing rain at Ottawa (validation dataset: Nov–Apr 1991/92–2000/01). Note that bold and italic data indicate the weather types most highly associated with freezing rain events.

Synoptic type			Freezing rain events								
			≥1 h			≥4 h			≥6 h		
Type	Days	Frequency (%)[a] (a)	Days	Frequency (%)[b] (b)	Ratio[c] (b)/(a)	Days	Frequency (%)[b] (c)	Ratio (c)/(a)	Days	Frequency (%)[b] (d)	Ratio[c] (d)/(a)
2	***110***	***6.07***	***12***	***12.63***	***2.08***	***5***	***11.36***	***1.87***	***2***	***8.00***	***1.32***
3	***131***	***7.23***	***31***	***32.63***	***4.51***	***16***	***36.36***	***5.03***	***10***	***40.00***	***5.53***
3	***142***	***7.84***	***29***	***30.53***	***3.90***	***15***	***34.09***	***4.35***	***8***	***32.00***	***4.08***
4	***106***	***5.85***	***8***	***8.42***	***1.44***	***4***	***9.09***	***1.55***	***3***	***12.00***	***2.05***
Subtotal[d]	**489**	**26.99**	**80**	**84.21**	**3.12**	**40**	**90.91**	**3.36**	**23**	**92.00**	**3.41**
5	61	3.37	0	0.00	0.00	0	0.00	0.00	0	0.00	0.00
6	134	7.40	0	0.00	0.00	0	0.00	0.00	0	0.00	0.00
7	134	7.40	2	2.11	0.28	1	2.27	0.31	1	4.00	0.54
8	86	4.75	0	0.00	0.00	0	0.00	0.00	0	0.00	0.00
9	71	3.92	4	4.21	1.07	1	2.27	0.58	0	0.00	0.00
10	67	3.70	0	0.00	0.00	0	0.00	0.00	0	0.00	0.00
11	128	7.06	0	0.00	0.00	0	0.00	0.00	0	0.00	0.00
12	75	4.14	0	0.00	0.00	0	0.00	0.00	0	0.00	0.00
13	140	7.73	1	1.05	0.14	0	0.00	0.00	0	0.00	0.00
Total[e]	1385	76.43	87	91.58		42	95.45		24	96.00	

[a] Represents percentage frequency of the weather type.
[b] Represents percentage frequency of the days with 1, 4, or 6 h or more freezing rain events within a particular weather type.
[c] Ratio of percentage frequency of the days with freezing rain events over the percentage frequency of the weather type. A number greater than one indicates that a larger proportion of days in the weather type possess freezing rain events than would be expected based only on the frequency of the weather type.
[d] Represents the sum of the four weather types identified as being most highly associated with freezing rain events.
[e] Represents the sum of the 13 weather types.

forecast of 70% is given, the freezing rain event should also be observed 70% of the time for the prediction model to be considered reliable. The results of the freezing rain prediction model, as shown in Fig. 3, indicate that there is good reliability for both developmental and validation datasets; however, the deviation from the perfect reliable line is greater for the validation dataset because of the smaller sample size (Wilks 1995).

Although major freezing rain events are relatively rare, we used the opportunity to test the model on data observed during a particularly severe ice storm that affected the northeastern United States and eastern Can-

TABLE 8. Breakdown by logistic regression probability for freezing rain events within weather types 1–4 at Ottawa (validation dataset: Nov–Apr 1991/92–2000/01). Note that bold and italic data indicate that threshold of logistic probability (≥0.6) can be used for prediction of freezing rain. The last row represents the percentage of the total freezing rain events that can be identified by the model using 0.6 as the logistic probability cutoff.

Logistic probability	Days without freezing rain			Days with freezing rain events				
	No precipitation	Snow/rain	Freezing drizzle	≥1 h	≥2 h	≥4 h	≥6 h	≥8 h
≥0.9	***2***	***0***	***2***	***22***	***20***	***17***	***10***	***7***
0.8–0.9	***0***	***1***	***0***	***8***	***8***	***8***	***5***	***3***
0.7–0.8	***1***	***0***	***2***	***1***	***1***	***0***	***0***	***0***
0.6–0.7	***1***	***1***	***1***	***4***	***4***	***2***	***2***	***0***
0.5–0.6	1	0	0	2	2	0	0	0
0.5–0.5	1	1	2	2	2	1	1	0
0.3–0.4	2	4	2	6	5	3	1	1
0.2–0.3	2	7	4	3	2	0	0	0
0.1–0.2	5	15	2	9	7	5	2	0
0.01–0.1	31	69	7	21	13	4	2	0
<0.01	39	47	2	2	0	0	0	0
FAR* (≥0.6)		***← 24% →***						
POD≥0.6)**				***44%***	***52%***	***68%***	***74%***	***91%***

* FAR: false alarm rate. The ratio is [1 − postagreement (PA)], where PA represents the number of correct predictions divided by the total number of predictions for freezing rain events, with a perfect PA equal to 1 (or 100%).

** POD: probability of detection represents the number of correct forecasts divided by the number observed in a category. Perfect probability of detection = 1 (or 100%).

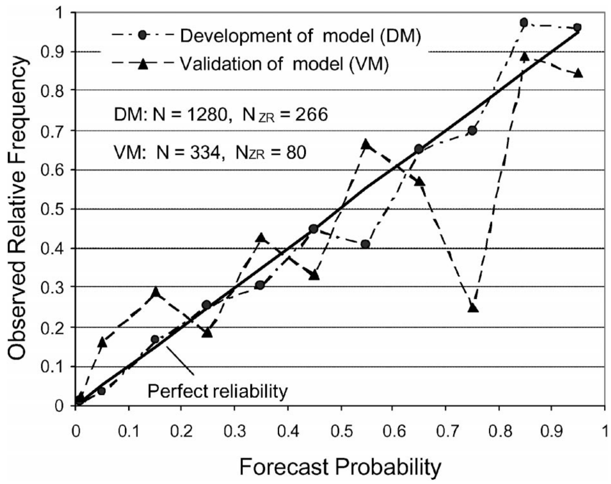

FIG. 3. Reliability diagram for probability of freezing rain forecasts summarized in Tables 5 and 8 for freezing rain events lasting 1 h or more during a day in Ottawa (N = number of sample days; N_{ZR} = number of freezing rain events).

ada, including the Ottawa area, during the period 5–9 January 1998. Within this 5-day period, the model correctly predicted the occurrence of freezing rain on all 5 days, with a very high probability >0.995 for the first 4 days, dropping to 0.68 for the final day. Interestingly enough, the weather types differed for the 5 days, with the first 4 days classified as type 2, and the final day classified as type 3. This change in classification and lowering in probability on the final day likely can be related to a transition in weather patterns during the day. By 0000 UTC on 10 January, the 500-hPa wind flow over Ottawa began to shift from a southwesterly to a more westerly direction (Environment Canada 1998), a less favorable direction for a flow of warm moist air and the occurrence of freezing rain.

e. Weather patterns of the identified freezing rain weather types

Using the automated synoptic typing procedure, four synoptic weather types have been identified as being most highly associated with freezing rain for Ottawa. Figure 4 illustrates the typical surface weather patterns and vertical wind, temperature, and dewpoint profiles associated with these four weather types. These patterns were compared to those identified by Rauber et al. (2001) using a manual classification approach. Each of the four weather types was found to be similar to one of the archetypal freezing rain patterns identified by Rauber et al. (2001). Weather types 1 and 3 are most similar to Rauber et al.'s PATTERN B (warm front–occlusion sector of cyclones). Weather type 2 is analogous to PATTERN C (cyclone–anticyclone couplets), while weather type 4 has similar traits to PATTERN D (west quadrant of Arctic high pressure). While each of these synoptic weather types is unique, they each possess some common traits that are typically related to precipitation ahead of surface warm/quasi-stationary fronts. A brief description of the meteorological characteristics and synoptic patterns associated with each of these weather types is outlined in Table 9.

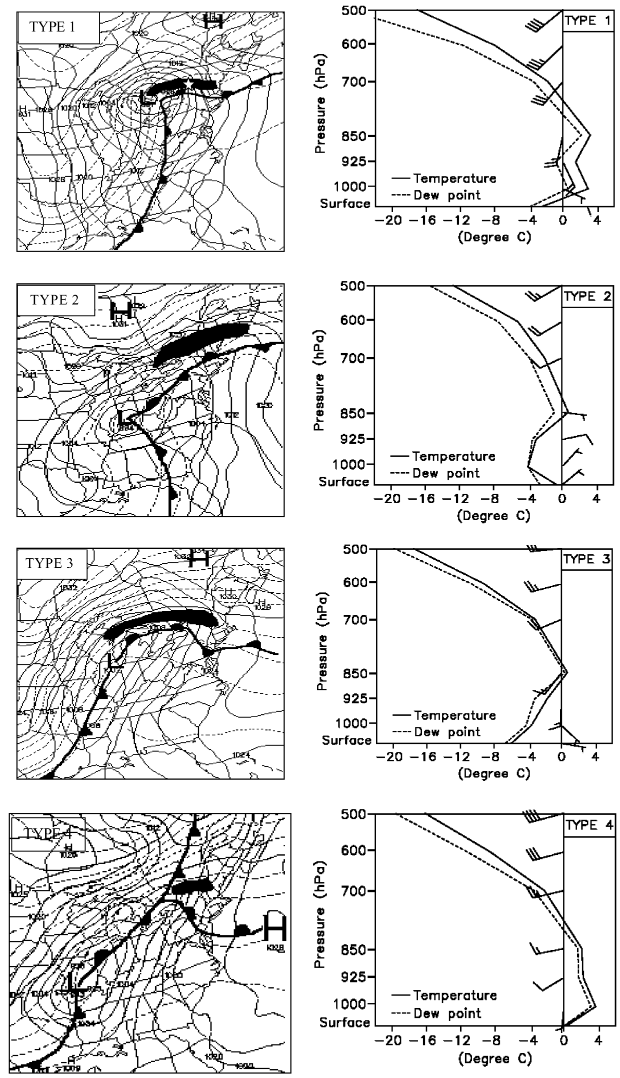

FIG. 4. (left) Archetypal surface synoptic weather patterns and (right) vertical wind, temperature, and dewpoint profiles associated with identified freezing rain airmass types. Black area denotes area of freezing rain. [Surface weather maps were retrieved from the Unisys Weather online map archive (http://weather.unisys.com/archive/eta_init) for 1200 UTC on 4 Jan 2000, 8 Jan 1998, 9 Feb 2001, and 21 Feb 1997 and represent weather types 1 to 4, respectively; the vertical profiles derived from the NCEP–NCAR reanalysis data and the surface observations are valid for the same time periods as the weather maps. The star on the Type 1 map indicates the location of the city of Ottawa.]

5. Conclusions and recommendation

This study utilized an automated synoptic typing procedure, consisting of principal components analysis, av-

TABLE 9. Meteorological characteristics and synoptic patterns within freezing rain–related weather types at Ottawa.

Weather type	Major meteorological characteristics (based on Tables 2 and 6)	Synoptic patterns	Frequency of long-duration freezing rain events (ZR)
1	● Low average surface pressures ● East-northeast surface wind ● Strong southwest winds at 700 hPa	● Frequently associated with rapidly moving and intense midlatitude cyclones ● Strength and orientation of the 700-hPa winds are indicative of an approaching upper-level trough and dynamic jet stream producing considerable upper-level divergence ● Intensity of low-level wind and thermal gradients produces strong warm air advection regime and convergence in advance of the surface warm front ● Duration of events is typically limited, but precipitation intensity can be significant with stronger forcing and potential for embedded convection ● Fairly shallow cold outflow from retreating high pressure center to northeast	ZR ≥ 6 h: 5% ZR ≥ 9 h: 0%
2	● Relatively high average surface pressures ● East-northeast surface wind ● Moderate west winds at 700 hPa	● Classic setup for prolonged freezing rain events ● West-to-east-oriented surface warm front often becomes quasi stationary as it aligns itself parallel to the upper (westerly) flow ● Nearly stationary Arctic high pressure center to the northeast maintains and can even strengthen low-level subfreezing layer ● Well-established moisture feed from Gulf of Mexico or Atlantic Ocean	ZR ≥ 6 h: 54% ZR ≥ 9 h: 61%
3	● Relatively high average surface pressures ● East-northeast surface wind ● Weak south-southwest winds at 700 hPa	This pattern is similar to Type 1 with the following differences: ● Typically slower moving and less intense midlatitude cyclones ● Strength of the 700-hPa winds and associated upper-level divergence are much weaker ● Duration of events is typically longer, but precipitation intensity is often lighter due to weaker synoptic forcing ● Colder surface temperatures and stronger surface outflow from Arctic high pressure center	ZR ≥ 6 h: 22% ZR ≥ 9 h: 29%
4	● Relatively low average surface pressures ● Southeasterly surface wind ● Moderate to strong southwest winds at 700 hPa	This pattern represents the "warmest" freezing rain weather type ● Surface temperatures are typically very close to the melting point during the event and can quickly rise above freezing after the passage of the warm front ● Southeasterly surface winds indicate only a weak or modifying "cold" outflow from a retreating Arctic high center to the east ● Longer-duration freezing rain events tend to be localized and are typically influenced by topographical factors such as cold air damming in valleys	ZR ≥ 6 h: 14% ZR ≥ 9 h: 10%

erage linkage clustering procedure, and discriminant function analysis, to identify and predict the specific synoptic types most conducive for freezing rain in Ottawa, Ontario, Canada. Four synoptic types were identified as being most highly associated with historical freezing rain events at this location. The model demonstrated significant skill in the discrimination and prediction of freezing rain events. These four synoptic types captured 81% and 84% of freezing rain events lasting 1 h or more during a day for the developmental and validation data samples, respectively. For freezing rain events lasting 6 h or more during a day, the results were more significant; the four weather types captured 97% and 92% of freezing rain events for the developmental and validation datasets, respectively.

Stepwise logistic regression was used to derive relationships between the observed occurrence of freezing rain and predictors computed from the surface weather observations and upper-air NCEP–NCAR reanalysis data. The regression model indicated that the following meteorological characteristics were most highly correlated with freezing rain occurrence at Ottawa: easterly–

northeasterly surface winds and southwesterly winds at midatmospheric levels, presence of a temperature inversion in the low to midatmospheric levels with air temperature aloft $>0°$ and $\leq 0°C$ at the surface, upward vertical velocity, falling sea level air pressure, high total cloud cover, 6-h temperature decreases near the surface and increases at midatmospheric levels (i.e., warm air advection), and dewpoint depression decreasing in the past 6 h (increasing moisture), both at the surface and midatmospheric levels. These weather conditions are consistent with a classical freezing rain scenario, providing the necessary ingredients to maintain a warm moist layer aloft and a cold layer near the surface.

Verification of the freezing rain prediction equation, for both developmental and validation datasets, indicated that the results were good and stable. The results have demonstrated that the logistic regression approach has significant skill in selecting freezing rain predictors and in predicting the occurrence of longer-duration freezing rain events such as those that would be associated with severe ice storms. The threat score is usually used for an evaluation of prediction, particularly when the forecast event (as the ‘‘yes’’ event) occurs substantially less frequently than the nonoccurrence (‘‘no’’) (Wilks 1995). The threat score is a ratio of the number of correct forecasts to the total number of occasions in which that event was forecast and/or observed, ranging from 0 to 1, where 1 represents a perfect forecast. Using the results in Tables 5 and 8, threat scores were calculated for freezing rain events ≥ 1 h with prediction probability ≥ 0.6 (yes event) and otherwise as a false alarm. Threat scores of 0.52 and 0.38 for the developmental and validation datasets, respectively, are better than the U.S. MOS threat score of 0.2 for a less-than-24-h prediction. However, MOS did show overall excellent discrimination ability for precipitation types (Heidke skill score = 0.86; ‘‘perfect forecasts’’ receive a score of one) (Allen and Erickson 2001).

The model may have significant potential for the prediction of severe or long-duration freezing rain events using the output from numerical weather prediction models to estimate the regression variables and to predict the future arrival of those weather types most highly associated with freezing rain events. For example, in Canada, numerical model output is available twice daily from the Canadian Meteorological Centre’s Global Environmental Multiscale model (with 28 vertical layers and 20-km horizontal resolution). There may be significant advantages to using MOS output variables as predictors to our model since the MOS approach tends to compensate for consistent biases and inaccuracies in the numerical model predictions (Carter et al. 1989). These model outputs, routinely available through to 48 h, include all of the standard meteorological variables necessary to assign each day into one of the preexisting weather types defined by the statistical synoptic typing procedure and hence, to predict the occurrence of freezing rain at the predictor site. If integrated into an operational forecast model, this freezing rain prediction model could serve as a useful tool to assist forecasters in predicting the occurrence of freezing rain, particularly for high impact and long-duration freezing rain storms.

In this study, the model was developed for only one location—Ottawa Airport, Ontario—one of the most freezing rain-prone areas in central Canada. Since the weather-typing structure and freezing rain prediction model developed for this study captures the synoptic and topographical influences specific to the Ottawa area, it should obviously not be applied to other locations. The characteristics of the thermodynamic stratification or reanalysis parameters observed at the time of freezing rain vary significantly from place to place (Robbins and Cortinas 2002). However, the methods, including weather typing and logistic regression, can be applied to any location influenced by a variety of topographic and other influences to build a new freezing rain prediction model.

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